Meta-Heuristic Algorithms in Car Engine Design: A Literature Survey

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***Abstract*—Meta-heuristic algorithms are often inspired by natural phenomena, including the evolution of species in Darwinian natural selection theory, ant behaviors in biology, flock behaviors of some birds, and annealing in metallurgy. Due to their great potential in solving difficult optimization problems, meta-heuristic algorithms have found their way into automobile engine design. There are different optimization problems arising in different areas of car engine management including calibration, control system, fault diagnosis, and modeling. In this paper we review the state-of-the-art applications of different meta-heuristic algorithms in engine management systems. The review covers a wide range of research, including the application of meta-heuristic algorithms in engine calibration, optimizing engine control systems, engine fault diagnosis, and optimizing different parts of engines and modeling. The meta-heuristic algorithms reviewed in this paper include evolutionary algorithms, evolution strategy, evolutionary programming, genetic programming, differential evolution, estimation of distribution algorithm, ant colony optimization, particle swarm optimization, memetic algorithms, and artificial immune system.**

***Index Terms*—Control system, engine calibration, engine management systems, evolutionary algorithms (EAs), fault diagnosis, memetic algorithms, meta-heuristic algorithms, multiobjective optimization.**

I. Introduction

MANY real-world problems can be formulated as optimization problems and many of them belong to the class of NP-hard problems [1], implying that no efficient algorithms exist to find their exact global optima. This has therefore encouraged the researchers to develop new sets of algorithms including meta-heuristic algorithms, which are often inspired by nature. Among these are evolutionary algorithms (EAs) that emulate the idea of the survival of the fittest mechanism in Darwinian theory of evolution. The advantage of these algorithms is that they require little prior mathematical information about the problems they are to solve.

Many population-based optimization algorithms [2]–[5] have emerged within the past few decades and have found their way into solving many optimization problems. One advantage of population-based optimization algorithms is the global search ability of the algorithms as the population consists of a number of individuals who are in cooperation with others search the solution space and share their knowledge about the problem [6], [7]. These optimization algorithms, also known as meta-heuristic algorithms, can be categorized into two main groups, the EAs including genetic algorithms [8], evolution strategy [9], evolutionary programming [10], genetic programming [11], [12], differential evolution [13], [14], estimation of distribution algorithm (EDA) [15], and swarm intelligence algorithms including ant colony optimization [16], particle swarm optimization (PSO) [17], bees algorithms [18], and bacterial foraging optimization [19]. Population-based algorithms also include memetic and cultural algorithms [20], harmony search [21], artificial immune systems [22], and learnable evolution model [23]. Since proposed, these algorithms have been successfully adopted to solve many different problems in different areas from engineering to ecology to the social sciences [24]–[27]. Due to their great performance and applicability, meta-heuristic algorithms have been applied in many aspects of engine management systems. In this paper, we review the application of these algorithms in car engine management systems. The aim of this paper is to broadly cover applications such that a global view toward the state-of-the-art on this topic can be obtained. The review also enables us to identify potential gaps in the literature and relevant future research directions.

Many optimization problems arise when designing automobile engines [28]–[32]. Most of them involve multiple conflicting objectives. The goal in these kind of problems is no longer to find a single best solution, but rather a set of solutions representing the best trade-off among the objectives. In this respect, the goal in these problems is to identify a set of efficient (Pareto-optimal) solutions.

One of the most important stages in engine design is engine calibration [33]–[40], which is the adjustment or modification of an internal combustion engine or its control unit with the goal of achieving the optimal performance in terms of engine power, fuel economy, emissions, and durability. In other words, the problem is a multiobjective one with sometimes contradictory objectives. The calibration is performed on different parts of the engines including air intake, ignition timing, and valve timing.

The engine control unit is an important part in an engine that controls a series of actuators with the goal of reaching the best performance. The control system reads values from a set of

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sensors and, by interpreting the data using multidimensional performance maps, manages the engine actuators. There are a number of control systems in an engine, including air-to-fuel-ratio control, idle speed control, start-up engine control, charge control, engine speed control, and fuel injection control. Optimizing the engine control systems is an important task in designing car engines.

Engine fault diagnosis [41]–[45] is the act of finding faults arising in different parts of an engine. To find the faults in engines, some data about the engine condition are gathered and then processed to find the possible causes. Different methods are used to collect the data, including vibration monitoring, thermal imaging, and oil particle analysis. Then different algorithms are utilized to process these data, which include wavelet transform, wavelet analysis, Winger–Ville distribution, cepstrum, bi-spectrum, correlation methods, spectral analysis, and short-term Fourier transform. Many optimization problems occur in fault diagnosis of engine systems and a lot of research employs meta-heuristic algorithms when dealing with these problems.

Another area of research in engine design is modeling different parts of the engines [46]–[53]. Modeling is performed for different reasons. One example is the design and optimization of a controller system. Designing a controller by using the real engine in the design process is an expensive and time-consuming task. Thus, many researchers first build a model of the engine and then design, test, and optimize their controller on this model. One other application of the models is for prediction, where the model of the engine is built and used to predict different behaviors of the engine in different environments. Optimizing different parts of an engine is yet another use of models, as optimizing the real engine directly is usually a time-consuming task, and it is easier to build a model and then optimize the parameters based on the engine model. Because of these wide ranges of applications of engine models, designing the best models is important and has been the focus of a lot of research.

The rest of this paper is organized as follows. Section II describes applications of meta-heuristic algorithms in engine calibration. Section III reviews the algorithms in optimizing the control systems of engines. Applications of meta-heuristic algorithms in engine fault diagnosis are covered in Section IV. Meta-heuristic algorithms in optimizing different parts of engines are discussed in Section V. Section VI surveys the current work in engine modeling, and finally Section VII concludes this paper. Table I shows the structure of this paper.

II. Engine Calibration

The strict conditions imposed on the production of car engines, like the CO_2 emission and fuel consumption, has made the calibration of engine control system more and more important. At the same time, because of the increasing complexity of the calibration task and the huge measurement efforts, traditional calibration methods begin to fail. Many car engine companies are investing in new methods of engine calibration [54]. In this section, we review the literature employing metaheuristic optimization approaches in engine calibration.

A. Control Unit Calibration

In engine calibration, the optimization cycle is decomposed into a set of stationary operation points of the engine based on its speed and torque. Then for each of these operating points the best parameters are found. The functions defining these parameters on the whole engine operating points are called the engine maps. Choosing the smoothest map from a given family of maps in engine control unit calibration is an optimization problem that belongs to the class of NP-hard problems [55]. The characteristic of this problem makes it appropriate for local search heuristics and other meta-heuristic algorithms. In the first major study in this area a memetic algorithm, which combines a genetic algorithm and local search was adopted in [55] to solve the problem.

Apart from using local search, the operators of genetic algorithms, like crossover, can also be manipulated to improve the performance of the algorithm. For example, in [56] and [57], it was shown that three process steps in engine calibration could be regarded as optimization problems that would benefit from genetic algorithms. The first step is the D-optimal experimental design, which is optimized with a local search algorithm and an appropriate crossover operator. The second step is the optimal test bed scheduling which can be seen as a traveling salesman problem and was solved by a hybrid genetic algorithm with 2-opt heuristic local search. And finally, the third problem is the look-up table which was optimized through a genetic algorithm. This method was successfully applied to a BMW engine in Munich [56]. Combining global and local optimization, a new hybrid algorithm called Multistoch was proposed for engine calibration in [54]. In this method, a fixed number of starting points, called grid, are generated for a local optimization procedure, and using a Gibbs measure, a point in the grid is selected. This selected point is then used to generate a new candidate point according to its fitness and modify the grid.

The other way of improving the performance of the algorithm is to benefit from statistical properties of the solutions. The optimization of the engine control unit mapping was targeted in [58], where a model of an integrated engine vehicle was developed. Then a distance-based Pareto genetic algorithm and a nondominated sorting genetic algorithm (NSGA), together with an entropy-based multiobjective EA (MOEA), were proposed and implemented on the engine model to optimize the engine with the objectives of reducing emission and fuel consumption. The results demonstrated the superiority of this method over the manual mapping methods. In [59], a combination of a genetic algorithm and an evolution strategy was used for the automatic calibration of a virtual engine of a BMW engine.

Combining different algorithms is a way of taking advantage of both the algorithms. One effort in this area is to take advantage of different multiobjective evolutionary optimization algorithms. A combined scheme was proposed in [60], which dealt with the difficulties in finding the optimal solution set during the engine calibration process. The method used a real-coded representation in the genetic algorithm and an elitist strategy was applied to each MOEA. The algorithms were

TABLE I
STRUCTURE OF THIS PAPER

ENGINE CALIBRATION	A. Control Unit Calibration	
	B. Air-Intake Calibration	
	C. Ignition Timing	
	D. Valve Timing	
	E. Diesel Engines	
	F. Hydrogen Fuelled Engines	
CONTROL	A. Air-Fuel Ratio Control	
	B. Idle Speed Control	
	C. Start-up Engine Control	
	D. Real Time Control Optimisation	
	E. Charge Control	
	F. Engine Speed Control	
	G. Fuel Injection Control	
	H. Control in Non-Gasoline Engines	1) Controlling Diesel Engines
		2) Controlling Hybrid Electric Engines
		3) Controlling Hydrogen Fuelled Engines
		4) Controlling Natural Gas/Hydrogen Engines
FAULT DIAGNOSIS	A. Engine Fault Diagnosis	
	B. Crankshaft Fault Diagnosis	
	C. Misfire Diagnosis	
	D. Oil Fault Diagnosis	
	E. Fault Diagnosis in Diesel Engines	1) Valve Fault Diagnosis
		2) Piston Pin Fault Diagnosis
		3) Fault Diagnosis of Fuel Systems
	F. Monitoring	
OPTIMISATION	A. Emission and Fuel Consumption	1) Emission in Gasoline Engines
		2) Emission in Diesel Engines
		3) Emission in Natural Gas Engines
	B. Optimisation of Fuel Consumption	1) Chemical Kinetic Model
		2) Fuel Economy in Gasoline Engines
		3) Fuel Economy in Diesel Engines
		4) Fuel Economy in Bio-diesel Engines
		5) Fuel Economy in Hybrid Electric Engines
	C. Optimisation of Mechanical Parts in Gasoline Engines	1) Air Cooling System
		2) Crankshafts
		3) Cylinder Fin Arrays
		4) Journal Bearing
		5) Engine Piston Design
		6) Engine Valve Design
		7) Intake and Exhaust Systems
	D. Optimisation of Mechanical Parts in Diesel Engines	1) Chamber Optimisation
		2) Heat and Power system
		3) Piston Bowl Optimisation
		4) Rubber Mount Displacement
		5) Injection Nozzles
	E. Optimisation of Mechanical Parts in Hydraulic Hybrid Engines	
	F. Optimisation of Mechanical Parts in Natural Gas Engine	
	G. Shape Optimisation	1) Piston Bowl Geometry Optimisation 2) Combustion Chamber Geometry Optimisation 3) Intake Ports Optimisation 4) Exhaust Manifold Optimisation
	H. Conversion	
MODELLING	A. Modelling Gasoline Engines	1) Sensor Systems
		2) Prediction
	B. Modelling Diesel Engines	1) Engine Models
		2) Cylinder Pressure
		3) Emissions
		4) Combustion
		5) Injection Pressure
		6) Prediction
		7) Pressure in Injection Pipe

applied to a calibration problem with the goal of minimizing the brake specific fuel consumption (BSFC) and to maximize the output power torque simultaneously. Wu *et al*. [60] reported a good performance for their proposed method.

Some researchers combine two different optimization algorithms, so the weaknesses of one algorithm is covered by the advantages of the other one. In traditional engine compensation map calibration, the parameters are normally set by trial and error as it is almost impossible to derive the exact mathematical model of the system. A new multiinput/output least-squares support vector committee machine was proposed by Wong *et al*. [61] to construct the engine compensation control system models on some experimental data. The authors employed a nonlinear regression algorithm to reduce the dimension of the parameters of the engine control system before the modeling stage. Then genetic algorithms and PSO algorithms were applied to parameter optimization to determine the optimal calibration maps.

One important problem in calibration is the parameter estimation for the model of the intake system of engine. The problem is multiobjective, which was tackled in [62] by a new combination of a genetic algorithm and an evolution strategy. The hybrid algorithm combines the covariance matrix adaptation of the mutation with the S-metric selection for the multicriteria fitness assignment of the individuals. The S-metric selection is a time-consuming process, specially when the problem has many objectives. However, the engine calibration problem is even more time consuming, which may take months or even years. In engine calibration, it is usually gathering the data from the real engine that is the most time consuming and financially expensive task, so employing S-metric might not significantly affect the total development time. The algorithm also uses a number of sub-populations and an intelligent DoE-strategy for the population initialization.

In Atkinson cycle engines, optimizing the fuel economy for part load is more important in reducing the total fuel consumption. In such engines, the intake valve closure timing, electrically throttling control, exhaust valve opening timing, spark angle, and air-to-fuel ratio affect the fuel economy. In order to optimize the fuel efficiency of an Atkinson cycle engine, in [63], some experimental data taken from various speed-load points covering the entire operating range were used to generate a neural model of the engine. Then a genetic algorithm was used to find the best parameters offering the most efficient fuel consumption. The experimental results demonstrated a greatly improved fuel economy across the operating range.

In engine calibration, not only the performance and emission under the current state have to be taken into account, but also maintaining the performance under various operating conditions is a matter of importance. Considering this, an adaptive self-learning control method was proposed in [64] and [65], which was based on heuristic dynamic programming. This paper used data from a test vehicle with a V8 engine to train a neural network controller which was used for controlling engine torque and exhaust air-to-fuel ratio.

B. Air-Intake Calibration

The air intake system of an engine controls the air fluid flown in the cylinder of an engine. It thus has an important role in the fuel efficiency of an engine and needs careful calibration. The calibration of the air-intake system of a turbocharged engine was addressed in [66], where using experimental data from an engine, a model of the air-intake system was made. Then a MOEA was employed to find the best valve timing to optimize the fuel consumption rate, emission, and torque of the engine. The calibrations were done over all the operation points and the results of the model-in-the-loop showed that the in-cylinder air mass estimations were in good agreement with the engine simulator under different transient operations. In [67], the ignition timing optimization of a bi-fuel spark ignition (SI) engine was targeted, where an artificial neural network was used to model the system. Then a constrained PSO was employed to optimize the ignition timing with the objective of optimizing the performance with the constraint of CO and NO_x emissions.

C. Ignition Timing

One of the most important tasks in calibration of an engine is the ignition timing which affects the fuel efficiency and emissions. A genetic algorithm was employed in [68] to optimize the injection timer of a gasoline engine. Multiobjective optimization of ignition timing of an engine using alternative fuels, CNG, and gasoline, was studied in [69]. A MOEA with the objectives of maximizing torque and minimizing exhaust gas was developed, which improved the NO_x, HC, and CO emissions while the torque loss was less than 5%.

D. Valve Timing

Valve timing is another optimization task that affects the performance of engines. In order to optimize valve timing of an engine, a PSO algorithm was employed in [70], where a thermodynamics simulation of the engine was used to evaluate the fitness of the particles. The algorithm optimized the major valve timing events, with the constraint of knock limit and maximum valve lift of 10 mm, where the objectives are the power output and the thermal efficiency. Traditionally, valve timing has been optimized to improve the torque and power curve, and reduce the fuel consumption and emissions. Variable valve timing is a new way of optimizing the performance. In [71], a neural network system was developed to model the effects of intake valve-timing, engine speed, torque, and fuel consumption of a gasoline engine. Then a MOEA was employed to optimize the variable valve timing. In [72] and [73], the optimization of a CAMPRO 1.6L engine valve timing at various engine speeds was performed, where a MOEA was employed with the objective of reducing emission and fuel consumption.

E. Diesel Engines

Engine calibration is also an important step in designing diesel engines. Similar to calibration in gasoline engines, the optimization cycle in diesel engines is described by engine maps. The difficulties associated with the engine map design and engine calibration were described in [74] and [75] and a MOEA was proposed. The authors applied their method to a real data set obtained from a diesel engine in their automated test-bench.

The calibration of a diesel engine was addressed in [76] where the parameters of an engine were tuned to optimize the emission and fuel efficiency. In order to optimize the engine, a neural network model of the engine was developed over a wide range of the engine operations. Then using the model, the parameters of the engines are optimized using a MOEA.

To calibrate a diesel engine, a global emulator-based Kriging model of the engine was used by Brahmi *et al*. [77] to predict the engine response, and then a genetic algorithm was adopted to give the best setting of parameters and optimize the fuel consumption within constraints of the NO_x emission. The authors believed that the main advantage of their method was its capacity to take into account a considerable number of controllable parameters without sacrificing the accuracy of the model prediction.

In order to reduce the complexity of the objectives in the calibration process, a new method was proposed in [78], which identifies and exploits local harmony between the objectives to reduce the number of objectives. In this method, a systematic process was designed to cluster the Pareto-optimal front and apply a rule-based principal component analysis for objective reduction. They applied this method to a diesel engine calibration optimization problem with six objectives and resulted in three- and four-objective sub-problems. Applying this method, a significant improvement was reported in one of the retained objectives at very little cost to the others.

F. Hydrogen-Fueled Engines

In hydrogen-fueled engines, analyzing and resolving the contradiction of abnormal combustion and improving the engine power are very important in promoting the engine's performance. An optimal model of hydrogen-fueled engine under the whole operating conditions of a hydrogen-fueled engine was developed in [79], which is a combination of nonlinear programming and optimal evolutionary calibration. In the proposed method, the calibration process could be adjusted dynamically to match with the working condition of an engine; thus, it not only simplified the calibration process, but also improved the calibration speed.

III. Control

A growing number of conflicting requirements on vehicle engines, like fuel consumption, emission, and engine performance, constantly increase the complexity of control and regulation tasks in engine control unit design. This vast complexity makes the conventional optimization approaches inapplicable and thus new sets of methods are required to solve these problems. Meta-heuristic algorithms have been used in solving optimization problems of engine control systems. Different algorithms were applied to different problems in the control unit design. In this section, we review such research.

In designing engine controller systems, the optimization methods must cope with uncertainties in the objective function and a limited number of fitness evaluations. To reduce the number of fitness evaluations in optimizing an engine control system, a new genetic algorithm was proposed by Sano *et al*. [80], which utilizes the history of search. In this method, the value of fitness function at a novel search point was estimated by the sampled fitness value at the point and by utilizing the fitness values of individuals stored in the history of search. The authors applied their method to an engine simulator and showed that their proposed method outperformed conventional genetic algorithms. Optimizing the control system of a particular engine model at a fixed working point via genetic algorithms was performed by Sun *et al*. [81], where different genetic algorithms were employed and compared in solving the problem. The authors tested their algorithm on a real engine.

A. Air-to-Fuel Ratio Control

Air-to-fuel ratio affects the power, torque, speed, emission, and catalytic efficiencies in engines. Thermal efficiency leads to low fuel consumption, while a high catalytic efficiency results in a low exhaust emission [82]. Although the catalyzers provide a good treatment for the exhaust gases, there still exists a need toward high performance air-to-fuel ratio controllers.

In order to improve the performance and reduce emissions of a 5.3L V8 engine, a novel heuristic dynamic programming algorithm was proposed in [83], which estimates cost function derivatives to design a more informed dynamic optimization algorithm. A neural network was employed in the research to estimate the derivative of the cost function. Their goal was to track the commanded torque and to regulate the air-to-fuel ratio at specified set points. As the oxygen sensor of gasoline engines was installed into the vent-pipe, there was a delay in the air-to-fuel ratio signal when reaching the control system. To overcome this, using an adaptive extended PSO a new air-to-fuel ratio predictive control method was proposed in [84]. To improve the global convergence of the algorithm, a multiparticle strategy and an adaptive control of the algorithm's parameters were used. Using data acquired from a HQ495 gasoline engine, the algorithm was tested on a simulation of the engine and the results suggested an improved performance when using the predictive control system.

B. Idle Speed Control

Idle speed control of engines is to stabilize the engine speed at a desirable level. The aim is to prevent the crankshaft from oscillating, as it results in vibrations of the components of the vehicle body. A number of researchers have employed meta-heuristic algorithms in idle speed control of car engines. In one of the first attempts in this regard [85], a fuzzy control was proposed for the problem. They then used the covariance matrix adaptation evolution strategy to optimize the model and the controller parameters. In [86], to control the idle speed of a SI engine, a directly identified nonlinear inverse of a stable system was proposed. The stable identification method was implemented by prediction error minimization using a genetic algorithm for which the model simulation was used to evaluate an root mean square (RMS) error performance function.

Most research in idle speed control has been to control the long-term averages of engine speed, but short-term fluctuations of engines stemming from the torque differences among cylinders has been neglected by many researchers. One of the first research targeting this issue was [87], in which two intelligent control systems were introduced. The intelligent systems were an evolutionary controller based on genetic algorithms and a stochastic controller based on the Alopex algorithm. The Alopex algorithm is a stochastic parallel algorithm which was originally suggested in [88] for visual receptive field mapping. In this method, first by observing the engine cycle of crankshaft angular speed, the torque differences among the cylinders was estimated. Then the uniformity level over the engine speed was feedback into the control system and the SI timing was manipulated to suppress any unbalanced combustions among the cylinders. The authors tested their system on a simulation of a nonlinear engine model and reported good performance.

The proportional integral derivative (PID) controllers are widely used in many fields and a number of methods to tune the parameters of the controllers have been proposed. One of these methods was proposed in [89] and [90], where a modified back propagate network by PSO was combined with a PID controller. The experimental results showed the superiority of their proposed method over traditional controllers.

C. Start-Up Engine Control

Engine start-up control is another control problem in car engine design. One example of applications of meta-heuristic algorithms in this area was [91] and [92], in which a feedforward controller was proposed for engine start-up and a PSO algorithm was used to optimize the input parameters of the controller.

D. Real-Time Control Optimization

Since the optimization algorithms used in engineering control units are often based on computationally expensive set of model equations, it is usually impossible to use real-time optimization in real-world applications. A new real-time optimization method was developed in [93], where the model equations of an engine control unit were replaced by a reduced model based on higher order singular value decomposition (HOSVD). The work does not propose a new optimization algorithm, but presents a method to improve the real-time performance of existing methods. When optimization requires the computation of a large number of states of the system, the proposed method computes the states of the system using HOSVD and describes the multidimensional properties of the physical system with faster equations, making it possible for real-time applications. A genetic algorithm was employed to optimize the working parameters of a SI reciprocating engine. Their goal was to find some engine control parameters that yield the expected engine power while minimizing the specific fuel consumption and avoiding knock combustion instability. The authors believed that their method was resilient enough to replace the genetic algorithm by any other optimization algorithm and it could be applied to other engineering systems.

E. Charge Control

The challenging feature of charge control in spark-ignition engine makes the problem very hard for many control algorithms. The charge control of a spark-ignition engine was addressed in [94], where by using a hybrid evolutionary-algebraic search algorithm that combines linear matrix inequalities (LMI) techniques based on K-S iteration with evolutionary search, a PID controller was proposed for the problem. The controller was applied to standard electronic control unit of a test car and showed promising results.

F. Engine Speed Control

Engine speed control is a nonlinear problem and it is often difficult to achieve the desired effect when using the conventional PID controllers. To control the speed of an engine, a neural PID controller was proposed in [95], and then a genetic algorithm was adopted to optimize the parameters of the controller. Improved engine performance was reported.

G. Fuel Injection Control

Having replaced the carburettor fuel injection has become the primary fuel delivery system in car engines. The fuel injection control was studied in [96], where the objective was to improve performance and reduce emissions. In this research, first a neural network model of the engine is designed, and the initial controller is trained using the model. The controller was then optimized using action-dependent heuristic dynamic programming.

H. Control in Nongasoline Engines

1) Controlling Diesel Engines: Diesel engine control parameters were optimized in [97], where a modified multiobjective PSO and a crossover approach were adopted. The authors addressed the optimization of the BSFC, exhaust gas emission, and soot. An engine speed control system of a diesel engine was developed in [98], where a fuzzy neural network system was used for the controller and a genetic algorithm was used to optimize the controller. In [99], the advance angle of injection, the opening angle of intake valve and the opening angle of exhaust valve of a diesel engine were calculated to get the virtual test sample of the engine. They then employed a genetic algorithm to optimize three parameters aiming to improve the economic efficiency under the constraint of the maximum pressure in cylinder and the exhaust temperature [99].

2) Controlling Hybrid Electric Engines: Hybrid electric engines benefit both from an internal combustion engine and an electric engine. If electric power is available the vehicle uses the electricity, and when it is not the petrol fuel is used. One important elements in improving the performance of hybrid electric vehicles is the careful selection of the control strategy parameters of the engine, which influences the fuel economy and emissions. To optimize the control parameters of a hybrid electric engine, a PSO algorithm was used in [100]. Management of the energetic flows in a hybrid vehicle is also a matter of importance. In order to maximize the use of the electric engine of a Toyota Prius engine while minimizing the use of the internal combustion one, increase the driving pleasure, and reduce emissions and noise, a genetic algorithm was employed in [101], which finds the optimal parameters of the control system of the engine.

Maintaining a stably generated electrical output in a hybrid vehicle generator set is a crucial task. The generator set consists of a three-phase ac generator, the output of which is rectified to dc. The system time delay makes the control integration of the engine/generator combination more complex and is usually solved by model predictive design methods. The predictive methods add computational complexity to the system and rely on accurate system and delay models. To overcome this delay problem, genetic programming was used to design a controller [102], which does not rely on the computationally expensive structures and yet encompasses the disturbance rejection properties.

Another type of electric vehicles are the plug-in hybrid electric vehicle which differs from hybrid electric vehicles in that they can use off-board electricity generation to recharge their energy storage systems. In order to optimize the control parameters in plug-in hybrid electric vehicles, a PSO algorithm was used in [103], where the fitness function was defined so as to maximize the vehicle engine fuel economy. In this method, the driving performance requirements were considered as constraints. The method was tested via computer simulations and experimental results showed improvements in fuel economy.

3) Controlling Hydrogen-Fueled Engines: Hydrogen-fueled engines have great advantages over other combustion engines; so it is expected to be widely used in future engines. However, due to the unique physical and chemical characteristics of the fuel, it often leads to abnormal combustion and decay of power unless the control parameters are carefully set. Meta-heuristic algorithms have often been used in controlling hydrogen-fueled engines. In [4], an optimization control model was proposed for a hydrogen-fueled engine which employed a MOEA to optimize the relationship between power, economy, emission, and operating parameters of the engine. In [104], after analyzing the mechanism of preignition and backfire of hydrogen-fueled engines, a multivariable, multiobjective, and multiconstraint genetic algorithm was proposed to optimize the control parameters of the engine. Through their experimental analysis, the authors showed that the method was capable of resolving the contradictions between restricting the abnormal combustion and improving hydrogen-fueled engine's power output. In [105], in order to manage the abnormal combustion and performance index of hydrogen-fueled engines, a theoretical analysis on the engines was provided to find the optimal control parameters. Using nonlinear programming and a MOEA, a control model was then designed and the optimal value of the operating parameters were found.

4) Controlling Natural Gas/Hydrogen Engines: In order to optimize the control parameters of a natural gas and hydrogen-fueled engine, a flexible model of the engine was developed, and then a genetic algorithm was used to optimize the model [106]. Finally, a multiobjective optimization genetic algorithm is used to optimize the engine with the objective of reducing the CH_4, CO, NO_x, and BSFC.

IV. Fault Diagnosis

The automobile engine faults was responsible for around 40% of all the car malfunctions [107]. Many intelligent algorithms have been developed for the problem and many of them employ evolutionary computation approaches. In this section, we review the papers that use meta-heuristic optimization approaches in engine fault diagnosis.

A. Engine Fault Diagnosis

A fault diagnosis method was proposed in [108], which used the wavelet transform to decompose the engine signal and then feed the decomposed components to a neural network. A genetic algorithm was then used to optimize the parameters of the neural network. The fault diagnosis problem of the vibration parameter is addressed in [107], where an adaptive neural network-based fuzzy inference system was developed. A hybrid gradient descent genetic algorithm was used to speed up the learning process. The experimental results provided in this paper showed that the method outperformed other neural networks in stability, recognition rate, and fitting capability. To reduce the number of inputs to an engine model, in [109] and [110], a parallel PSO algorithm was adopted to the selection of a feature subset. A uniform mutation operator was used in the optimization algorithm to balance the particles search ability. Using this method, they showed that the fault recognition system could reach 98.72% accuracy [109], [110].

B. Crankshaft Fault Diagnosis

A bending deformation of the shaft results in a great deal of stress on the joint point of the carrier and planetary gear shaft and thus affecting the engine performance. To diagnose the faults associated with the crankshaft of an automobile engine, a combination of a probability causal model and a genetic algorithm was proposed in [111], which could quickly and accurately diagnose engine failures.

C. Misfire Diagnosis

The engine misfire is a common fault in engines, which results in air pollution and low fuel efficiency. Therefore, much research was performed in this area to diagnose the problem. In [112], an intelligent algorithm was proposed for misfire diagnosis in engines, where support vector machine (SVM) was used to extract the volume fractions of the engine emission. They then employed a genetic algorithm to optimize the parameters of the SVM.

D. Oil Fault Diagnosis

The oil fault diagnosis of an engine was investigated in [109], where an adaptive neural network-based fuzzy inference system was employed and a hybrid gradient descent genetic algorithm used to optimize the parameters of the neural network and speed up the learning process. The authors reported good results, where the fault detection accuracy was 98.99%.

E. Fault Diagnosis in Diesel Engines

In order to diagnose the faults in a diesel engine, a radial basis function (RBF) network was used in [113]. Then based on a clonal selection algorithm, a dynamic clustering algorithm was adopted to specify the initial positions of the RBF centers and an immune EA was employed to train the network. In [114], the vibration signals from a diesel engine were collected and then wavelet packets analysis coefficients of vibration signals were used to evaluate their Shannon entropy. These coefficients were then used as features to diagnose the faults of the engine. The data were then fed to a back-propagation neural network, and a hybrid PSO algorithm with a differential operator were adopted to adjust the weights of the network. In a similar approach [107], the cylinder vibration signal of a diesel engine was extracted and transformed into the wavelet coefficients. Then a back propagation genetic algorithm neural network method was employed to diagnose the faults in the engine.

1) Valve Fault Diagnosis: In engine fault diagnosis systems, the features extracted from one type of faulty signals usually overlap with the ones collected from other faulty signals. This makes the problem of diagnosing the faults complicated. Thus, effectively finding the most discriminative features and the adoption of a powerful diagnosis strategy are two important ingredients of a good diagnosis algorithm. Considering these two aspects, in order to develop a diagnosis algorithm for valve fault diagnosis of a diesel engine, a genetic algorithm was proposed in [115] to find the best features, and then the Kernel principal component analysis technique was used for the diagnosis purpose. The algorithm was tested on the sixth exhaust valve of a 6135-type diesel engine, and the results showed effective performance. In a rather similar work, in order to diagnose the faults in a diesel engine, an ant colony algorithm was adopted in [116] to simplify the attribute parameters reflecting the operating conditions of the diesel engine, and then a RBF neural network was used to diagnose the faults. In [117], genetic programming was employed to diagnose the faults of the valves of a six cylinder/four stroke cycle diesel engine in three different valve states: the normal condition, valve-tapped clearance, and gas leakage faults. The authors applied a power-weight coefficient to each feature to construct the diagnostic tree more intelligently. They designed 22 mathematical functions and eight signal features to construct the diagnostic model. Additionally, they employed different evolution strategies for selecting the functions and features.

2) Piston Pin Fault Diagnosis: In order to diagnose the fault feature extraction of piston-pin of a diesel engine, a genetic neural network was employed in [118]. As the features of nonstationary vibration signals cannot easily be extracted, the bispectrum analysis technique was studied in this research, where the bispectral characteristics frequency faces are searched along the parallel to the diagonal line at certain steps in the bispectral modulus field. Then the mean magnitude was calculated to obtain the feature parameters.

3) Fault Diagnosis of Fuel Systems: The fault diagnosis of the fuel system in a diesel engine was addressed in [119], where using a bootstrap, the data acquired from a running engine were preprocessed. Then a genetic programming algorithm was developed which finds an efficient tree-like structure of a group of initial candidate features. The proposed algorithm in this paper found the best compound feature and showed promising results.

F. Monitoring

The importance of many internal combustion engines whose work condition affects the performance of a car, makes the monitoring of the engines an effective way to prevent the costly faults. As the vibration signals from a diesel engine reflect the condition of the engine, they can be used by pattern recognition algorithms to monitor engine conditions. In [120], the vibration signals from a diesel engine were captured and the characteristic features of the signals were extracted in the amplitude, time, and frequency domains to form the features. Then, a genetic algorithm was employed to find effective features which were more representative of different conditions of the engine and to reduce the feature space dimension. The authors used self-organization feature mapping as the pattern classifier. In [121], genetic algorithms were employed in an engine configuration monitoring task, where visualization of parameter sets for PID controllers, data clustering, and detection of outliers were used. The method was tested by statistically generating parameters for PID through a genetic algorithm. To design the fitness function, an ideal reference signal was considered, then the difference between the output signal and the ideal signal was set to be the error. Another example of the applications of meta-heuristic algorithms in condition monitoring of an engine is presented in [122], where a boundary optimization gradient genetic algorithm was employed.

Fault diagnosis is an important problem that arises in many aspects of any type of car engines. Due to its complexity, many different techniques including neural networks, SVMs, and fuzzy systems have been developed. To optimize these methods, different meta-heuristic optimization techniques have been employed that were covered in this section.

V. Optimization in Other Areas

A. Emission and Fuel Consumption

In this section, we review meta-heuristic algorithms for emission minimization. The section is organized around the engine type.

1) Emission in Gasoline Engines: Undesired generation of radiated or conducted energy in electrical systems is called electromagnetic interference (EMI). A new meta-heuristic algorithm for optimizing the emissions of an automobile SI engine was proposed in [123]. The method used EMI simulation models and a micro-genetic algorithm to optimize the parameters and variables of an engine. Experimental results showed that the performance of the micro genetic algorithm was superior to that of other optimization algorithms.

2) Emission and Fuel Consumption in Diesel Engines: Using the phenomenological model of a diesel engine and a multiobjective optimization problem, the specific fuel consumption, NO_x, and soot of the engine was optimized in [124]. The aim was to design the shape of injection rate. They performed simulations and showed the capability of the genetic algorithm in finding good results. They then extended their optimization algorithm in [125], where a MOEA called SPEA2+ was used for optimizing the emission and fuel economy of the engine. A genetic algorithm was employed in [126] to reduce the emission and fuel consumption of a diesel engine. The engine control parameters were boost pressure, exhaust gas recirculation, start of injection, and injection rate shape. In order to optimize the control map of hydrocarbon addition to diesel exhaust gas for HC type selective catalytic reduction (SCR) $DENO_x$, a numerical model and a new optimization technique were adopted in [127]. The numerical model presented in this paper predicted the performance of $HCDeNO_x$ with diesel fuel as a supplemental reductant and an evolutionary programming algorithm optimizes the control map of HC. Through experiments, they showed that the NO_x

conversion with the optimized control map was found to be 21% greater than that of the conventional control. In order to reduce the emission levels of a diesel engine, a MOEA is employed in [128], to optimize the combustion chamber profile of the engine. The authors performed the numerical simulations with a modified version of the KIVA3V code to evaluate the fitness values of the solutions. In [129] and [130], in order to reduce the exhaust emission of a diesel engine, the geometry of a diesel engine combustion chamber was optimized by a combination of genetic algorithms and PSO algorithms. A large database of stationary engine tests covering a wide range of experimental conditions of a diesel engine were used in [131] to model the engine. An artificial neural network was used, where the engine operating parameters were fed to the network as inputs and the outputs were the resulting emission levels and fuel consumption. The neural network was then used for fitness evaluation purpose and a genetic algorithm was used to optimize the emissions and fuel consumption of the engine. In [132], optimizing the performance of a diesel engine was investigated with the objective of optimizing NO_x emission, soot, CO, HC, ISFC, and peak PRR. A genetic algorithm was used by adjusting six parameters: the boost pressure, EGR rate, fraction of premixed fuel and start of late injection timing. In order to reduce emissions while maintaining the performance in both single and double injection strategies, PSO was used in [133]. They showed that the NO_x and PM emissions were reduced when their proposed method was used. In [134], single and MOEAs were used for optimization of performance and emissions of a diesel engine.

In diesel engines, there is a trade-off between the fuel economy and NO_x values. Developing the diesel engines which can adapt themselves with the environment could be a step forward. Therefore, there is a need to Pareto solutions that can express the trade-off between the fuel economy and NO_x emissions. To cover a variety of driving conditions, the dominated solutions should had a wide diversity not only in the objective space, but also in the design variable space. To perform this, a MOEA called SPEA2+ was used in [125] to design a diesel engine. The results showed that the solutions have a diversity not only in the objective space but also in the design variable space. They showed that an engine could be designed to adapt their parameters to the changing in driving environment.

The NO_x emission reduction of a diesel engine was addressed in [135], where the Euro steady state calibration test data set was used to make a neural model of the SCR catalytic converter for each chosen condition. In order to generate sufficient data for each condition, a mathematical model of the SCR converter was run. Then these neural models, in conjunction of a MOEAs were used with the objective of reducing NO_x and limiting the outlet ammonia concentration of the SCR catalytic converter.

Other examples of the application of meta-heuristic algorithms in reducing diesel engine emissions includes the use of PSO in [136].

3) Emission in Natural Gas Engines: In order to reduce the NO_x emission of a natural gas engine, genetic algorithms, and neural networks were employed in [137]. In this paper, to calculate the amount of NO_x emissions of a natural gas engine, a neural network model was developed, the validity of which was then verified by measurements from a turbocharged, lean-burn, and natural gas engine. The results of the model were then used to study the effects of the operational and design parameters of the engine. Using a genetic algorithm, the parameters of the engine were optimized to reduce the NO_x emissions. Their experimental results suggested that their proposed method could reduce the NO_x emissions down to 250 mg/Nm^3 for stationary engines.

B. Optimization of Fuel Consumption

In this section, we review the research which use meta-heuristic algorithms in order to optimize the fuel efficiency of car engines.

1) Chemical Kinetic Model: In order to fulfil the new stringent regulations on limiting pollutant emissions new concepts like the homogeneous charge compression ignition (HCCI) have emerged [138]. Unlike in traditional compression ignition and SI engines, these combustion modes are controlled by the fuel chemical kinetics leading to autoignition. The combustion process in HCCI engines does not involve flame propagation as in SI engines or flame diffusion as in diesel engine. Thus, the combustion in HCCI engines is dominated by fuel/air chemical kinetics [138]. In this respect, a detailed model of the fuel oxidation chemistry is essential in modeling the engines. One example of applications of genetic algorithm in this area is [139] and [138], where a new reduced chemical kinetic model of *n*-heptane was developed. After developing a model for the problem, a micro-genetic algorithm was employed to adjust the parameters of the model. In [140], the Shell hydrocarbon fuel ignition model was improved, where the 26 kinetic parameters of the model were optimized using a genetic algorithm guided by results obtained from a detailed kinetic mechanism. The optimizations were performed for a wide range of conditions representing the operating conditions in diesel engines.

In HCCI engines, the detailed reaction mechanism of surrogate fuels cannot be used for engine simulation purposes, due to very expensive computational time requirements [141]. Therefore, some algorithms were used to reduce the reaction mechanisms, among which were genetic algorithms that offered an efficient reduction of reaction mechanisms. In [141], a genetic methodology for the reduction of kinetic mechanisms was proposed which provided very similar results to those obtained from the detailed mechanism.

2) Fuel Economy in Gasoline Engines: In order to optimize the fuel economy of a gasoline engine under emission constraints, in [142] the variable valve timing and variable compression ratio techniques under various operating regions were applied to a 1.8 L four-cylinder engine. The authors use a genetic algorithm for the speed-load points for potential maximal and minimal fuel economy benefit via technology synergy. In [143], a neural network was developed to model a gasoline engine. Then a PSO and a derivative-based method were used to minimize the fuel consumption of the engine with respect to the constraint of emission.

3) Fuel Economy in Diesel Engines: In order to optimize the fuel consumption of a diesel engine, under constraint of NO_x emission, a genetic algorithm was used in [144]. In this paper, first using Kriging model, an emulator of the diesel engine was developed and then the genetic algorithm was applied to optimize the parameters. A MOEA was employed in [145], where the fuel consumption and engine emissions of a diesel engine were simultaneously optimized. In [146], a multiobjective optimization algorithm was adopted to improve the BSFC, and simultaneously minimize NO_x and soot emissions of a diesel engine. In order to reduce the fuel consumption for stoichiometric diesel combustion in a diesel engine, a micro-genetic algorithm was employed in [147], where the optimization parameters were the injection strategy, spray included angle and initial conditions like temperature and pressure. This optimization yielded 11.8% improvement in fuel consumption with simultaneous deduction of soot, NO_x, CO, and HC.

4) Fuel Economy in Bio-Diesel Engines: Determining the optimal bio-diesel blends has a great deal of effect on the fuel economy and emissions of a bio-diesel engine. In order to find the best bio-diesel blend and speed ranges of a diesel engine, a neural network was first developed in [148] to model and predict brake power, BSFC, and the emissions of engine. Then a NSGA in conjunction with a diversity preserving mechanism called the ϵ-elimination algorithm was used to perform the optimization process on the model of the engine. The authors considered six different objectives and used a TOPSIS-based method to find the best solution. In [61], the optimal bio-diesel ratio with the goal of achieving fewer emissions and reasonable fuel economy was found. Using different advanced machine learning methods including extreme learning machines, least-square SVMs, and radial-basis function neural networks, a model of the engine was generated and then subject to different constraints and using simulate annealing and PSO to optimize the best bio-diesel ratio.

5) Fuel Economy in Hybrid Electric Engines: In order to minimize the fuel consumption and emissions of a HEV, PSO was employed in [149]. Considering the driving performance requirements as constraints, the component sizing of the engine were optimized in this research. One of the main steps in designing a HEV is to select the power train topology which affects the fuel economy and performance of the engines. In this respect, in order to find the best topology for a HEV offering the best fuel economy and power train cost, PSO, and dynamic programming were employed in [150]. They applied their algorithms to HEV engines with three degrees of freedom: the size of the engine, the motor, and the battery.

C. Optimization of Mechanical Parts in Gasoline Engines

Designing mechanical structures is a complex optimization task with different and sometimes contradictory objectives. This is particularly true when designing different parts of a car engine. Many researchers thus employ meta-heuristic algorithms when designing mechanical parts of an engine. In this section, we review the applications of meta-heuristic algorithms in mechanical design of car engines. We start our review with applications of heuristic algorithms in designing mechanical parts of gasoline engines.

1) Air Cooling System: In order to optimize the air-cooling system of an engine, a multiobjective EA was employed in [151]. In this problem, there were two conflicting objectives, one was the volume of the required material for construction of the finned cylinder and the other was the heat release per unit temperature difference. The system they have designed generated a set of solutions, thus users can select the optimal geometric configurations based on their project requirements.

2) Crankshafts: In one of the first attempts in employing meta-heuristic algorithms in crankshaft design, a genetic algorithm was used in [152] to determine the design unbalance of crankshafts and also to optimize the geometric shape for balanced design of crankshafts. They then extended their study in [153]. The crankshaft-bearing system of a four-cylinder engine was designed in [154], where a PSO algorithm was used to optimize the crankshaft mass and the total average frictional power loss of the crankshaft bearing. The results suggest 26.2% and 5.3% reduction in average frictional power loss and crankshaft mass, respectively. In order to optimize the crankshaft offset a genetic algorithm was used in [155]. The optimization process in this paper was defined to be the minimization of friction losses between piston and cylinder, and the difference between peak values of resultant force of the piston in the normal direction. The research showed that the performance of an engine can be improved by a careful offset of crankshaft.

3) Cylinder Fin Arrays: Genetic algorithms were used in cylinder fin arrays is the maximization of heat transfer through fin arrays of an engine cylinder [156], where a binary coded genetic algorithm was employed. They also studied the effect of spacing between fins on various parameters.

4) Journal Bearing: Targeting the optimization process of journal bearing design, a MOEA was employed in [157]. The optimization goal in this research was to minimize friction loss and lubricant flow as the two main objectives in journal bearing design. The authors first developed a neural network which models the journal bearing system. The optimization was then performed using the model.

5) Engine Piston Design: One problem in engine piston manufacturing is the definition of sample size in attribute control charts. This problem was addressed in [158], where a model was developed to determine the best acceptance probability and to provide the minimum cost in every stage. A genetic algorithm was then used to solve the model, using the objectives of sample size and acceptance number.

6) Engine Valve Design: In many real-world manufacturing problems, there are many parameters such as defective item rate for raw materials and benches, which dynamically change due to human factors, operating faults, or other reasons. A fuzzy approach was developed in [159] for attribute control charts, and a genetic algorithm was employed to optimize the sample size and acceptance number of the model.

7) Intake and Exhaust Systems: One way of reducing the emission of new engines is through the post-processing techniques, such as installing a catalyst in the exhaust pipe. However, the problem with this technique is that the exhaust pipe changes the reflection point of the exhaust pressure wave, which decreases the torque of the engine. This could be managed by optimizing the intake and the exhaust pressure wave. A genetic algorithm was adopted in [160] to optimize the intake and exhaust system of a gasoline engine, where the experimental data were used to model the engine, then the length and diameter of the intake and exhaust pipes were optimized.

The control of the intake's manifold pressure of a gasoline engine was studied in [161]. This paper proposed a novel control architecture for tuning the H_∞ engine controller, which was optimized by a PSO algorithm.

D. Optimization of Mechanical Parts in Diesel Engines

In this section, we review the applications of meta-heuristic algorithms in designing mechanical parts of diesel engines.

1) Chamber Optimization: In order to optimize the chamber geometries, with the objective of reducing emission level and fuel efficiency, a micro genetic algorithm is developed in [162]. The authors designed a distributed version of the algorithm and speeded it up using grid computing technologies to show how a parallel environment could be used to reduce the computational time. The optimization of combustion chamber of a diesel engine was studied in [163] and a hybrid EA was proposed consisting of a genetic algorithm and a PSO.

2) Heat and Power system: The combined heat and power system of a diesel engine was optimized using a genetic algorithm [164]. The system was first thermodynamically analyzed through energy and exergy and then an objective function was considered representing the fuel cost, cost of energy loss and distribution, purchase, and maintenance cost of the system. Experimental results provided in this paper showed 8.02% improvement in the objective function when using the genetic algorithm.

3) Piston Bowl Optimization: Reactivity controlled compression ignition (RCCI) is a combustion strategy which offers low NO_x and PM emissions and high thermal efficiency. In [165], a genetic algorithm was employed in order to optimize the bowl surface area of a diesel engine. The authors showed that using this method, the RCCI brake efficiency was increased by 3% and NO_x and PM emissions were met.

4) Rubber Mount Displacement: In combustion engines, the unbalanced forces of rotating and reciprocating parts cause vibrations. These vibrations could be isolated with help of rotating balancing disks attached at both ends of the crankshaft. The masses of the balancing disks and their lead angles determine the effectiveness of the isolation. In this respect, in order to minimize the vibrations, the masses and lead angles of the disks can be optimized, e.g., using genetic algorithms [166].

5) Injection Nozzles: The injection nozzle in a diesel engine have a significant effect on the engine's combustion and therefore optimizing its configuration is an important step in improving the fuel consumption and emission of the engine. A PSO algorithm was used in [167] in the process of configuring injection nozzles.

E. Optimization of Mechanical Parts in Hydraulic Hybrid Engines

The shortage of energy and pollution concerns have made the use of hydraulic hybrid vehicles more promising. In these engines, the key component sizes have a great deal of effect on the performance and fuel economy of the vehicles. A multiobjective optimization method based on a hybrid simulated annealing and genetic algorithm was proposed in [168] to optimize the key components in hydraulic hybrid vehicles, where in the objective function, all the weighing factors can be set with different values according to different requirements.

F. Optimization of Mechanical Parts in Natural Gas Engine

In order to design an optimized injection system for a compressed natural gas engine, a multiobjective evolutionary optimization algorithm was developed in [169]. The Kriging meta-models were used in this paper to approximate the expensive objective function.

G. Optimization of the Performance of Engines

The performance of an internal combustion engine is affected by different settings of the basic parameters. Optimizing the performance of a vehicle engine using a hybrid genetic algorithm was performed in [168], where the heat loading, mechanical loading, and the conditions of gas mixture of the engine and boundary constraints were optimized.

H. Shape Optimization

A number of papers have used meta-heuristic algorithms to optimize the geometric shape of some parts of engines.

1) Piston Bowl Geometry Optimization: Different versions of genetic algorithms were compared in [170], to optimize the piston bowl geometry, spray targeting, and swirl ratio. The experimental studies presented in this paper suggested that NSGA II [171] performed better than the other algorithms. This was then improved in [172], where NSGA II was studied using different niching strategies applied to the objective and design spaces. This mechanism diversifies the optimal objectives and design parameters. The piston bowl geometry, spray targeting, and swirl ratio of a diesel engine were optimized in [173], using a MOEA. An adaptive multigrid chemistry model is developed and the numerical results from the model were used in the optimization process. The objectives in the optimization process were reducing the fuel consumption and pollutant emissions.

2) Combustion Chamber Geometry Optimization: The combustion chamber geometry and engine operating conditions for a stoichiometric diesel combustion was optimized in [174], where the aim of the optimization was to reduce the specific fuel consumption. The optimization algorithm used was a micro genetic algorithm, where the combustion chamber was represented by ten variables. Experimental results suggested a 35% improvement in the specific fuel consumption.

The same method was also applied to optimize the chamber geometry of an engine fueled with dimethyl ether with the objective of improving the merit value [175]. A 136% improvement in merit value was reported to be achieved during the optimization process.

3) Intake Ports Optimization: The intake ports in a diesel engine affects the performance of an engine. A parallel evolutionary optimization algorithm was used in [176] to optimize the intake ports geometry of a diesel engine.

4) Exhaust Manifold Optimization: The exhaust gas of engines should be kept at a high temperature in the exhaust pipe as the catalyst located at the end of the exhaust pipe absorb more pollutant at a high temperature. Therefore, designing the shape of an exhaust pipe of engines is an optimization process which affects the amount of pollutants. A multiobjective optimization design system of exhaust manifold shapes of a car engine was proposed in [177] and [178], where a divided range MOEA was used with the objectives of optimizing engine power and exhaust gases. An engine simulator coupled with the unsteady Euler code was used in the optimization.

I. Conversion

When converting an engine from diesel to CNG, different optimization problems occur, for which meta-heuristic algorithms can offer good results. One example was [179], in which two optimization problems associated with engine conversion were solved. One was the engine configuration, which is to find the best configuration with the objectives of optimizing the fuel economy while avoiding detonation. The other was to find the best possible combination of combustion chamber geometry. Both problems were solved by MOEAs.

VI. META-HEURISTICS IN MODELING

Previous sections have touched upon how engine modeling has been used in aiding optimization, especially in providing fitness evaluation for meta-heuristic optimization algorithms. Additionally, meta-heuristic algorithms have also been used to optimize the models. This section reviews further work along these lines since these are very common practices in work related to engine design, calibration, maintenance, and fault diagnosis.

A. Modeling Gasoline Engines

1) Sensor Systems: A hot-film mass air-flow system sensor used in automobile engines to measure the intake mass airflow was studied in [180]. In this method, a novel approach for modeling the sensor system was proposed and PSO was proposed to optimize the model. The experiments performed showed the effectiveness of PSO in finding the parameters of dynamic sensor models.

2) Prediction: In order to predict the torque and BSFC of a gasoline in terms of spark advance, throttle position and engine speed, a genetic programming-based model of the engine was developed in [181]. Experimental data were gathered and used to train and test the system. The results presented in this paper suggested that the proposed method was comparable to neural network modeling systems in terms of speed, and accuracy.

B. Modeling Diesel Engines

Diesel engines can be modeled by the methods based on the first law of thermodynamics or the computational fluid dynamics. However, there are deficiencies in these methods, e.g., an insufficient accuracy at some ranges of engine work cycle and the difficulties in applying to real-time control. Therefore, computational intelligence methods are introduced which can provide promising results.

1) Engine Models: Computer simulations of internal combustion engines are very important in studying the engines; however, because of the uncertainty of input parameters, the models are not very precise and thus the model parameters should be calibrated. Calibrating the parameters of the model of a diesel engine was studied in [182], and a hybrid genetic algorithm and ant colony optimization algorithm were employed. The aim of the research was to reduce the time of calibration process and improve the precision of the model. In order to develop a four-cylinder diesel engine model, the ANSYS software was used [183]. Then grid meshes were imposed to the model with contact-setting and boundary conditions and PSO was employed for the flatness error analysis.

2) Cylinder Pressure: Concerning the measurement and modeling cylinder pressure in a diesel engine, an analytical-empirical model of the engine was built in [184]–[186]. A genetic-fuzzy algorithm was used in this papers to model the system. In [187], an empirical-analytical model for diesel engine operation and control was built using a genetic-fuzzy system. The system was used to simulate the cylinder pressure of a diesel engine fueled by bio-fuels or diesel oil, for each allowable crankshaft speed.

3) Emissions: A genetic programming-based evolutionary system identification algorithm was proposed in [188], to model the formation of NO_x and particulate matter emissions in a diesel engine. The model was then compared to other models designed by experts. The authors showed that genetic programming modeling approaches were capable of generating models which can be used as global virtual sensors. In [189], a novel control-oriented model of raw emissions of diesel engines was presented. The inputs of the model were chosen by a selection algorithm which was based on genetic-programming. Then based on the selected inputs, a hybrid symbolic regression algorithm generated the nonlinear structure of the model. Experimental results suggested that while the proposed model had a smaller number of inputs, it provided comparable results to those obtained with neural networks.

4) Combustion: In order to build a parametric model of combustion in a combustion chamber of a diesel engine, differential evolution, and evolution strategies with different fitness definitions were studied in [190].

5) Injection Pressure: A model of cylinder and injection pressure in a diesel engine fueled by rapeseed methyl esters or its blend with diesel oil was built in [191]. In this research, a data of 50 working cycles and 512 measurement data for

TABLE II
REVIEWED PAPERS CATEGORIZED-BASED ON THE OPTIMIZATION ALGORITHMS AND APPLICATIONS

Algorithm	Application	Papers Reviewed
Memetic Algorithm	Calibration	Control Unit Calibration [54]–[56]
Hybrid Gradient Descent GA	Diagnosis	Engine Fault Diagnosis [107], Oil Fault Diagnosis [109]
	Monitoring	Monitoring [122]
Hybrid GA and ES	Calibration	Control Unit [59], [62]
Hybrid GA and EA	Optimisation of the Performance	Optimisation of the Performance of Engines [169]
Hybrid GA and PSO	Calibration	Control Unit Calibration [61]
	Emission	Emission in Diesel Engines [130], [131]
	Optimisation	Chamber Optimisation [164]
Hybrid GA and SA	Optimising Mechanical Parts	Mechanical Parts in Hydraulic Hybrid Engines [169]
Hybrid GA and Ant Colony	Modelling	Diesel Engine Models [183]
Elitist GA	Calibration	Control Unit Calibration [60]
GA	Calibration	Control Unit Calibration [63]
	Ignition Timing Optimisation	Gasoline Engines [68], CNG and Gasoline Engines [69]
	Engine Optimisation	Diesel Engines [77]
	Control	Gasoline [81], Diesel [98], [99], Hybrid Electric [101], Natural Gas/Hydrogen [106], Real Time [93] Engines Idle Speed [86], [87], Engine Speed Control [95]
	Fault Diagnosis	Engine [108], Crankshaft [111], Misfire [112], Valve [115], Piston Pin [118], Diesel Engines [107] Fault Diagnosis
	Monitoring	Gasoline Engine [120] [121]
	Performance Optimisation	Heat and Power system [165], Natural gas engine [138], Chemical Kinetic Model [141], [142], Intake and Exhaust Systems [161]
	Emission	Emission in Diesel Engines [124], [125], [127], [132], [133]
	Fuel Economy	Gasoline [143], Diesel Engines [145]
	Optimising Mechanical Parts	Crankshafts [154], [156], Cylinder Fin Arrays [157], Piston Bowl [166], Rubber Mount Displacement [167]
	Design	Engine Piston [159], Engine Valve [160]
	Modelling	Cylinder Pressure [185]–[188], Injection Pressure [192]
		Pressure in Injection Pipe [195]
	Prediction	Prediction [193], [194]
GA history of search	Control	Engine Control [80]
Heuristic Dynamic Programming	Calibration	Control Unit Calibration [64], [65]
	Control	Air-to-Fuel Ratio [83], Fuel Injection [96]
Non-dominated Sorting GA II	Geometry Optimisation	Piston Bowl Geometry Optimisation [172] [173]
Diversity Preserving GA	Performance Optimisation	Fuel Economy in Bio-diesel Engines [149]
micro-genetic algorithm	Emission	Emission in Gasoline Engines [123]
	Fuel Economy	Fuel Economy in Diesel Engines [148]
	Optimisation of the Performance	Chemical Kinetic Model [139], [140]
	Optimising Mechanical Parts	Chamber Geometry Optimisation [163], [175], [176]
Multi-Objective GA	Control	Hybrid Electric Engines [104]
SPEA2	Emission	Emission in Diesel Engines [126]
Ant Colony	Diagnosis	Valve Fault Diagnosis [116]
PSO	Control	Idle Speed [89], [90], Start-up Engine [91], [92], Hybrid Electric Engines [100], [103] Control
	Fault Diagnosis	Engine Fault Diagnosis [109], [110]
	Fuel Economy	Fuel Economy in Hybrid Electric Engines [151]
	Optimising the Performance	Intake and Exhaust Systems [162]
	Mechanical Parts	Injection Nozzles [168], Crankshafts [155]
	Modelling	Sensor Systems [181], Diesel Engine [184]
	Calibration	Valve Timing Calibration [70]
	Emission	Emission in Diesel Engines [134]
Derivative based PSO	Fuel Economy	Gasoline Engines [144]
Differential PSO	Fault Diagnosis	Fault Diagnosis in Diesel Engines [114]
Multi-Objective PSO and Crossover	Control	Diesel Engines [97]
Hybrid Simulate Annealing and PSO	Fuel Economy	Fuel Economy in Bio-diesel Engines [61]
Multi-Objective EA	Calibration	Air-Intake [67], Valve Timing [71]–[73], Control Unit [58] Diesel [74]–[76], [78], Hydrogen-fuelled Engine [79] Hydrogen-fuelled Engines Control [4], [105]
	Emission	Diesel Engines [135], [136]
	Fuel Economy	Diesel Engines [146], [147]
	Conversion	Conversion [180]
	Optimising the Performance	Air Cooling System [152]
	Mechanical Parts	Combustion Chamber [129], Journal Bearing [158], Piston Bowl Geometry Optimisation [174], Exhaust Manifold [178], [179], Natural Gas Engine [170]
Adaptive extended PSO	Control	Air-to-Fuel ratio control [84]
Covariance Matrix Adaptation ES	Control	Idle Speed Control [85]
Hybrid Evolutionary-Algebraic Algorithm	Control	Charge Control [94]
GP	Control	Hybrid Electric Engines [102]
	Fault Diagnosis	Valve Faults [117], Fuel Systems [119]
	Prediction	Prediction [182]
	Modelling	Modelling Emissions [189], [190]
Immune EA	Fault Diagnosis	Diesel Engines [113]
EA	Emission	Diesel Engines [128]
Parallel EA	Mechanical Parts	Intake Ports Optimisation [177]
Differential Evolution and ES	Modelling	Combustion [191]

each working cycle of the engine were generated. Then a fuzzy system was used to model the system, and a genetic algorithm was used to optimize the fuzzy system.

6) Prediction: SVMs are shown to provide good results in condition prediction. However, when it comes to complex systems, like diesel engines, the results are not very satisfying.

Thus, a genetic algorithm was used in [192] to optimize the SVM in predicting the condition of a diesel engine. The genetic algorithm was used to select effective parameter combinations from the condition signal. Experimental data from a diesel engine were used to validate the model and showed good accuracy. In [193], artificial neural networks and RBFs were used for sound prediction of a diesel engine. In this paper, the training algorithm for neural networks was an EA.

7) Pressure in Injection Pipe: Using computational intelligence methods, the pressure in an injection pipe of a diesel engine was modeled in [194]. Several methods including a genetic fuzzy system and neuro-fuzzy ANFIS were employed. The models were compared and the experimental analysis suggested that the best method is the genetic fuzzy system.

Table II categorizes the reviewed papers based on the algorithms and applications. The most widely used algorithms are the genetic algorithm and PSO. This is because these two algorithms are easy to use and versatile. Other optimization algorithms like genetic programming, immune EAs, ant colonies, quantum EAs (QEA) [195], [196], etc., have gained less attention. Each of these optimization problems are suitable for different problem types. The following observations can be made on the table.

1) GP is suitable for structure optimization problems. For problems like crankshaft design, cylinder design, piston design, valve design, etc., this algorithm is more likely to provide good results.
2) Ant colony optimization is suitable for graph-based optimization problems. Among the reviewed papers, only one has used the algorithm for a fault diagnosis problem, although the problem is not a graph-based problem.
3) QEAs are suitable for combinatorial and binary coded optimization problems. Many optimization problems in car engine design are combinatorial or binary coded, so considering QEA is suggested.
4) Many optimization problems in engine design involve uncertainty. This happens when noise is involved or when a fitness approximation method is used. Some algorithms like covariance matrix adaptation evolution strategy and EDAs can be more suitable for these sets of problems.
5) Hybridizing optimization algorithms should be performed carefully. That is the two algorithms should complement one another. For example, when a problem is partially binary and partially graph-based hybridizing QEA and ACO algorithm can be attempted. Since car engines are very complex, we are very likely to encounter these set of problems.
6) Memetic algorithms are not recommended for uncertain problems. When a problem involves uncertainty, the local search algorithms can easily be distracted as the fitness of the neighbors of the current solution may change or be inaccurate during the search process. Therefore, optimization algorithms that are more powerful at capturing the global behavior of the landscape are recommended.
7) The properties of the fitness landscape of the problem should also be taken into account. Problems with a more rugged landscape are better managed with global optimization algorithms, while the ones with more smooth landscapes and less number of local optima are more easily solved with memetic and local search algorithms.

VII. Conclusion

Car engine design is an extremely complex task that involves many different but interlinked challenges, including those in optimization, modeling, control, etc. This paper focuses on challenges related to optimization only. In particular, we have limited ourselves to meta-heuristic optimization in car engine design, because of its effectiveness in solving hard and complex optimization problems. In order to gain an overview of what have been done in applying meta-heuristic optimization to car engine design, a comprehensive review has been carried out to understand where and how meta-heuristic algorithms were used in car engine design. We have categorized the research into five overlapping categories: 1) engine calibration; 2) optimization in control systems; 3) engine fault diagnosis; 4) meta-heuristic algorithms in modeling; and 5) mechanical part optimization.

In spite of the huge range of applications of meta-heuristic algorithms in car engine design, some interesting observations can be made.

First, there is a very close link between optimization and modeling. Almost all meta-heuristic optimization algorithms rely on an engine model for obtaining objective values, i.e., fitness values. This implies that the success of an optimizer, whether meta-heuristic or not, is not just an issue of a better and more powerful optimization algorithm. Instead, the success depends on both the optimization algorithm and modeling. Accurate models are essential in ensuring the success of optimization. At the same time, good optimization algorithms can help to learn/build more reliable and accurate models. While there has been much work on optimization and modeling separately, much fewer work has been on the interaction between optimization and modeling and their appropriate combinations.

Second, most of the work in car engine design involve multiple objectives. MOEAs were very widely used in car engine design, although a detailed analysis of when to use which MOEA is still lacking. There are still a lot of trial-and-error in selecting an MOEA for a particular problem.

Third, all the work in meta-heuristic optimization for car engine design implicitly assumes a static and deterministic optimization problem, while the real-world is dynamic and full of uncertainties.

Fourth, many works try to benefit from the nature of meta-heuristic algorithms and improve the performance of the algorithms when solving engine management problems. These could be categorized into three different groups. The first group use a hybrid of a meta-heuristic algorithm with a local search or another type of meta-heuristic algorithms. For example, in [55]–[57], [94], [107], [109], [143], and [168], a meta-heuristic algorithm is hybridized with a local search algorithm. Thus, the global search advantages of the meta-heuristic algorithm and the hill climbing and speed of local search are combined to achieve a better algorithm. Other examples of hybrid algorithms are [60], [97], [107], [129], [130], [163], [182], and [190], where two types of meta-heuristic algorithms are combined so the advantages of one algorithm covers the weakness of the other one. The second group are the works that improve the performance of the algorithm with operators. Improving crossover [56], [57] and mutation [62] operators, using history of search [80] and entropy in the individuals [58] to guide the individuals, preserving diversity among the individuals [148] and using niching strategies [172] are some examples of these works. The third group of works target the objective function. Some example of these are reducing the number of objectives to improve the speed [78], using neural networks to estimate the derivative of fitness function [83] and replacing the fitness function with high speed equations that makes the optimization real-time. Note that here, neural network or machine-learning techniques could be employed to model the real fitness function, or they may be used to improve the performance of the algorithm.

Despite the wide range applications of meta-heuristic algorithms, we believe there are still some ideas in the field of evolutionary computation which have not been adopted in car engine optimization. In this section, we try to suggest some research topics for future works.

Four main types of uncertainties were identified in fitness evaluation within the evolutionary computation community [208]. None was considered in car engine design. The first uncertainty is noise, which may come from different sources including sensory measurement errors or randomized simulations. To date, many EAs have been developed to deal with noise in EAs [197]–[200]. It is interesting to investigate the application of such algorithms to car engine design in the future. The second source of uncertainty is robustness. Sometimes the design variables are subject to changes after the optimization. Therefore, the optimal solution has to be robust to minor changes in the fitness function. Some examples of research in this area can be found in [201]–[204]. Fitness approximation is the third source of uncertainty in optimization problems. Some examples of the research trying to manage this uncertainty are [205]–[209]. The final source of uncertainty is the time-varying fitness functions, which occur when the fitness function itself may change as time progresses and has been studied in a number of research [210]–[216].

All these four types of uncertainties exist in automobile engine design problems. Some examples are as follows.

1) *Noise:* When trying to optimize the emission, the sensors measuring the gasses and particles may induce noise to the fitness function.
2) *Robustness:* Engines are some mechanical machines subject to ageing; thus, the input parameters to a controller change over time.
3) *Fitness Approximation:* Many papers reviewed in this paper used the meta-model approach for their optimization, i.e., they used an engine simulation model to approximate the real fitness values.
4) *Time-Varying Fitness Functions:* Engines work in an ever-changing environment; therefore, the fitness function changes with time, depending on different aspects of an environment.

Although these uncertainties occur in all the optimization problems in engine design, none of the research reviewed in this paper have developed algorithms to manage them. One of our future work is to tackle these uncertainties when optimizing automobile engines.

The second future work is to investigate the relationship between uncertainties and multiobjectivity in engine design, as the uncertainties can be addressed from a multiobjective point of view [217]. Some research suggested that multiobjective optimization problems, which occur in engine design in great number, can be converted into dynamic single objective optimization problems [218], [219]. Conversely, the concept of Pareto-optimality can be used to address fast changing dynamic optimization problems [220]. When converting a multiobjective problem to a dynamic single objective problem, different uncertainties may occur. First since the conversion is usually performed based on deterministic approaches, the noise uncertainty is less likely to occur due to the conversion. Second in terms of robustness, when the multiobjective optimization is converted to dynamic single objective optimization, there is usually some discrepancy between the two. One way of managing this uncertainty could be to make a model of the discrepancy using machine learning techniques. The model then can be used during the optimization to calibrate the fitness. The third class of uncertainty is fitness approximation that occurs during the conversion. Managing this type of uncertainty could be performed by measuring the uncertainty as proposed in [207], incorporating the uncertainty in the fitness function and reevalute the individuals with uncertainty higher than a threshold. Finally, since multiobjective problems are not necessarily time varying, when a multiobjective problem is converted to a dynamic problem, the fourth uncertainty is introduced to the problem. To deal with this type of uncertainty different methods could be used, including restarting the search, generating and maintaining diversity, using memory-based approaches and multipopulation methods.

The third future work is to further investigate memetic algorithms in automobile engine design, because they often provide a good framework for combining advantages of global search from a meta-heuristic algorithm and efficient local search. This scheme could specifically be useful when it is applied to engine calibration, when fitness evaluation is very expensive and usually a fitness approximation model of the engine is used. In this case, both the engine model and real engine could be used simultaneously. For example, since the local search performs exploitation and the evolutionary part acts for global exploration, the local search needs more accurate fitness estimation and the evolutionary part needs more general information of the landscape. Therefore, for the evolutionary part a faster and less accurate model could be used, and for the local search, a more accurate real engine can be employed.

When choosing an existing EA for a specific problem in engine management, a researcher should take the nature of the problem and the algorithm into account. For example some problems, like engine calibration, have a few number of optimization parameters so the search space is not very large, but evaluating the fitness function is very time consuming. In this case, the EA should be able to find a good solution with the minimum number of fitness evaluations, so a more exploitive EA with faster convergence is more suitable or employing some optimization algorithms like surrogate-assisted evolutionary techniques [221] could be tried. In some other cases, the problems have a large number of optimization parameters while fitness evaluation is less expensive. Here, the EA can perform a larger number of fitness evaluations and should perform a more global search, so a more explorative algorithm would be more suitable.

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